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A detour for snacks and beverages? A cross-sectional assessment of selective daily mobility bias in food outlet exposure along the commuting route and dietary intakes

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ABSTRACT

The evidence of selective daily mobility bias distorting exposure-health associations is limited. Using 7-day smartphone-based global positioning system (GPS) tracking data for 67 Dutch adults aged 25–45, we conducted paired Wilcoxon tests to compare the absolute and relative exposure to food outlets along actual and modelled commuting routes. We fitted Tobit regressions to examine their associations with three daily snack and soft drink intake outcomes. We found significant differences in absolute food outlet exposure between two types of routes. Adjusted regression analyses yielded unexpected associations between dietary intakes and food outlet exposures. Our results suggested no evidence of a selective daily mobility bias in the association between the food environment along commuting routes and adults' snacks and soft drink consumption in this sample.

1. Introduction

The food environment is considered a critical determinant of dietary behaviors (Caspi et al., 2012; Herforth and Ahmed, 2015). Unhealthy dietary intake characterized by increases in the consumption of low-nutrient and energy-dense foods has contributed, in Europe, to the increase in the prevalence of overweight from 53% in 2019 (Eurostat, 2021) to 59% in 2022 (World Health Organization, 2022). This increase threatens public health (Ng et al., 2014), calling for a better understanding of the interactions between the food environment and dietary intake.

Earlier studies have identified two potential mechanisms for how the food environment might be associated with dietary intake. One pathway relates exposure to food outlets to the direct consumption of food products at these food outlets (Mackenbach et al., 2019). At the same time, another indirect mechanism presumes that exposure to food outlets may not lead to immediate dietary behaviors (Van Rongen et al., 2020). However, there are inconsistent associations between food exposure and dietary intake in the evidence for these mechanisms, partly due to the inconsistent measurement of food exposure (Bivoltsis et al., 2018).

A typical measure of exposure to the food environment is the availability of food outlets within an area (Caspi et al., 2012; Bivoltsis et al., 2018; Lytle, 2009; McKinnon et al., 2009). Past studies primarily measured exposure to food outlets at home locations using different contextual units (e.g., administrative units or buffers centered on residential addresses) (Lytle and Sokol, 2017; Poelman et al., 2018). However, such approaches have been criticized for ignoring people's daily mobility outside their homes (Perchoux et al., 2013; Wei et al., 2023) and thus likely incorrectly estimating the actual food exposure in people's day-to-day lives (Chen and Kwan, 2015). To more accurately depict the actual exposure to the food environment, the use of the global positioning system (GPS) has been suggested to track people's daily mobility and their food exposure along actual travel routes accurately

Abbreviations: GPS, global positioning system; SDMB, selective daily mobility bias; GIS, geographic information system.

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and in fine spatial and temporal resolution (Clary et al., 2017); however, previously such an approach has rarely been realized in food environment studies (Cetateanu and Jones, 2016; Liu et al., 2020; Wang and Kwan, 2018).

Concerns about using GPS data for causal statements on health outcomes have mounted, which is articulated as the 'selective daily mobility bias' (SDMB) (Chaix et al., 2013). The SDMB refers to the situation in which people are more exposed to a certain environment due to making conscious decisions to conduct specific activities (Plue et al., 2020). While GPS records capture people's actual food exposure accurately, it remains largely unclear whether people are actively or passively exposed to the food environment (Plue et al., 2020). Active exposure is when exposure to a specific environment is attributable to individuals' intention to visit such locations (Chaix et al., 2013). This may lead to SDMB because the exposure also reflects intentional behavior in addition to objective exposure. Consequently, the observed exposure-health associations could potentially be erroneous as they can be the relationships between intentional behavior and the outcomes. One methodological choice that may induce a SDMB is using GPS-tracked routes instead of modelled shortest routes based on geographic information systems (GIS), which possibly mis-estimate exposure to food environments (Chaix et al., 2013). For example, individuals' possible purposeful travel route choices (e.g., preference for consuming fast food) might change their food exposure (e.g., to a particular fast food retailer). Such differences in route choice might increase exposure to the fast food environment. In turn, the food consumption-exposure to the fast food environment association might (wrongly) appear positive. However, as speculated by Zenk et al. (2011), the results of such observed associations are possibly overestimated due to the SDMB.

Although some studies have emphasized the potential influence of SDMB on environment-health associations (Cetateanu and Jones, 2016; Zenk et al., 2011; Kestens et al., 2012), only a few have empirically tested its existence (Burgoine et al., 2015; Klein et al., 2021). For example, Burgoine et al. (2015) examined the relationships between body mass index and fast food exposure along children's actual and shortest commuting routes. However, they found that using actual route exposure did not confound the exposure-body mass index associations. By contrast, Klein et al. (2021) tested the associations between environmental exposures along older adults' actual and shortest non-commuting routes and their detour behaviors. Their findings suggested a potential SDMB that people tend to choose travel-friendly environments.

However, these conflicting findings were based on population groups (i.e., children or older adults) with limited mobility. Children have restricted daily mobility as they are under the regulation and supervision of adults (Christensen et al., 2011). Their choices of school commuting routes, both to and from, are also determined by parents (Oluyomi et al., 2014). Similarly, the elderly often experience daily mobility impairment (Webber et al., 2010). By contrast, adults are autonomous and typically visit several activity locations along their daily commuting routes (Wei et al., 2023; Noland and Thomas, 2007; Ye et al., 2007). Consequently, the possibility of actively making choices to visit specific activity locations is greater among adults than any other age group, rendering them an ideal population group to examine possible SDMB.

To bridge the knowledge gap, we aimed to examine whether SDMB influences the associations between food outlet exposure to snacks and soft drinks along the commuting route and small snack intake, large snack intake, and soft drinks intake among young Dutch adults. First, we compared the differences in food outlet exposure based on GPS-tracked and GIS-modelled commuting routes. Second, we assessed the associations of captured food outlet exposure and dietary intakes between GPS-tracked and GIS-modelled commuting routes. Our first hypothesis was that the GPS-tracked routes had greater food outlet exposure than the GIS-modelled routes because we expect individuals to detour for snacks and soft drinks and thus have higher exposures. Second, we hypothesized that food outlet exposure was positively associated with dietary intakes, and the exposure along GPS-tracked routes more strongly associated with dietary intakes than modelled routes. If individuals detour because of their dietary preference for snacks and soft drinks, the associations between exposure and dietary intakes should be stronger on the route they actually undertook than the modelled route.

2. Materials and methods

2.1. Study design and participants

We conducted a cross-sectional analysis in the Netherlands as a part of the FoodTrack study (Poelman et al., 2020). In short, the FoodTrack study examines people's exposure to the food environment and its relation to their food choices. Eligible criteria for participation in the FoodTrack study were: 1) being between 25 and 45 years of age; 2) living in an urban area; 3) not being a full-time student; 4) owning a smartphone; 5) being free from physical disabilities, not having a gastric bypass, not having an eating disorder, not using a medicine that affects appetite, and not being on a prescribed diet. Between March and July 2018, adults ($N = 648$) were recruited via offline and online platforms (e.g., newspapers and Facebook). Respondents were asked to complete an online application form.

Participants who did not meet the eligibility criteria ($N = 414$) were discarded at this data collection stage. The remaining participants ($N = 234$) provided informed consent before completing an online baseline questionnaire on socio-demographics and some related dietary questions. In total, 143 participants were included and tracked with their GPS-enabled smartphones over 7 days, yielding a response rate of 58.8%. The study design was approved by the ethical committee of the Faculty of Social Sciences at Utrecht University (FETC18-014).

2.2. GPS data collection and preprocessing

After baseline questionnaire completion, participants received a text message including a link for downloading the FoodTrack smartphone app developed by Locatinent, the commercial company, from the App Store or Google Play (Broll et al., 2012). Another email provided the smartphone app log-in information and a randomly assigned tracking start day (i.e., Monday to Sunday). After a user granted in-app permission to monitor locational data, the app ran in the background. GPS-based location information was recorded every 30s, a typical sampling interval used in previous studies (Zenk et al., 2011; Tamura et al., 2018). When the device was stationary (i.e., a phone displacement less than <150 m), the location was recorded once per minute. If a displacement of >150 m relative to the prior location was detected, the app continued to record the locational data. If there was no displacement for 8 min, a trip session ended. The recorded trip data were transferred to a backend server at Locatinent for further processing (Bie et al., 2012). The transport mode of each trip (i.e., foot, bike, car, bus/tram, or train) was inferred based on trip characteristics (i.e., average, standard deviation, 95% quantile of speed, acceleration, and heading) using the C5.0 decision tree-based classifier (Kuhn and Quinlan, 2018).

2.3. Deriving commute routes

2.3.1. GPS-tracked routes

To derive daily commute routes, we initially excluded unemployed participants ($N = 9$) from the 143 study participants (Fig. 1). For the rest, we estimated their home and workplace locations based on GPS data as these details were not collected. We assumed that people spent most of their daily time (i.e., dwell time) in the first place at home and in second place at work (Chen et al., 2014). We also assumed that a minimum of two daily trips must be recorded between estimated home and

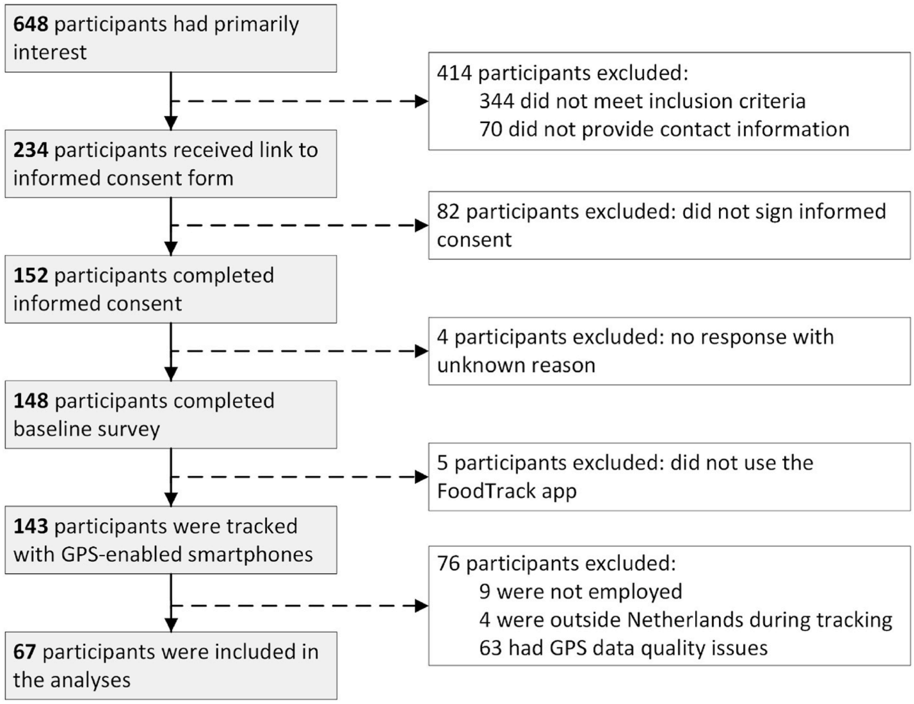

Fig. 1. Flowchart of participants of the FoodTrack study included in the Selective Daily Mobility Bias analyses.

work locations. We were unable to determine work and home locations for participants who travelled outside the Netherlands ($N = 4$) and for those with GPS data quality issues such as missing locational data ($N = 63$). For the other participants, the GPS-tracked trips from home to work (and vice versa) were determined. Trips were matched with the 2018 road network extracted from OpenStreetMap using the Leuven.Map-Matching (Meert and Verbeke, 2018) and OSMnx (Boeing, 2017) packages, available in Python 3.9.7.

2.3.2. Shortest path-based routes

Based on the common assumption that individuals seek to minimize daily commuting (Nuhn and Timpf, 2022; Rodríguez and Joo, 2004), we computed the shortest path between home and work for each travel mode during the tracking period (Dalton et al., 2015). We applied the following rules for modeling the mode-specific trips. All road network segments that pedestrians could traverse (except private roads and highways) were included for walking trips. For cycling and car trips, bicycle and car route networks were used. For public transport-based trips (i.e., train, bus, and tram), the shortest path route was computed in two steps. First, we considered the shortest train/bus/tram trip between the nearest stops to home and work because data on the exact routes in operation were not available. Second, the shortest path routes for the rest of the trips (i.e., between home/work and stops) were computed. The analysis was performed using OSMnx packages (Boeing, 2017). We reclassified the trips into active travel trips (i.e., walking, cycling), car trips, and public transport trips (i.e., train/bus/tram).

2.3.3. Trip characteristics

Two trip characteristics were determined to compare the GPS-tracked routes and the shortest path routes guided by earlier studies (Burgoine et al., 2015; Klein et al., 2021; Dalton et al., 2015). Route length (in km) was measured by the origin-destination distance along the road network. Detour percentage captured the difference in length between observed and modelled routes divided by the modelled route length. Both measures were computed for each commuting trip.

2.4. Food exposure

Food exposures were assessed based on food retailer data from 2018 obtained from Locatus, a commercial company that collects food retailers' information (e.g., location, size, and type) in the Netherlands. A field audit validated the data's geocoding and food type classification accuracy and found it to be 'good' to 'excellent' (Canalia et al., 2020). Guided by Mackenbach et al. (2022), we considered all supermarkets, bakeries, mini-markets (e.g., small grocery stores, convenience stores), gas stations, Toko (ethnic stores), sweet stores, and coffee/tea as food outlets where people could obtain snacks and soft drinks. We assessed food outlet exposures using 100 m Euclidean trip buffers, which is seen as an appropriate buffer size for capturing route-based characteristics (Panter et al., 2010), and 250 m Euclidean trip buffers for comparison. Similar buffer sizes have been used previously (Burgoine et al., 2015; Klein et al., 2021; Kestens et al., 2018; Seto et al., 2016). We adopted the following two measures to capture food outlet exposure: 1) The number of food outlets within the buffers (i.e., an absolute measure), and 2) the percentage of our target food outlets relative to the total number of all types of available food outlets (e.g., supermarkets, restaurants, café) within the buffers (i.e., a relative measure) (Mason et al., 2013; Clary et al., 2015). We determined the mean value of food outlet exposures over all measured trips for each participant as the participant's exposure level.

2.5. Environmental exposures

Commuting route choices, for other than personal purposes, could be conditioned by many factors related to the natural and built environments (Basu et al., 2021; Ye et al., 2007). As a result, such factors might steer commuters away from the shortest route (Zhu and Levinson, 2015). Thus, it was necessary to characterize route characteristics to understand people's route choices. We assessed three typical environmental exposures within 100 m and 250 m buffers (Klein et al., 2021; Böcker et al., 2017; Krenn et al., 2014).

Green space was assessed using the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979) applied to route-based buffers. We computed the NDVI with a 30 m spatial resolution using Landsat-8 imagery captured between May and September 2018. Images with cloud coverage >40% and pixels with cloud scores >25 were disregarded. NDVI values range from −1 to 1, with greater positive values indicating more vegetative cover. To avoid distortions of the results, pixels with negative values were masked before averaging the NDVI values for each buffer, as negative values represent areas covered by water.

Address density was calculated by dividing the number of buildings within the buffers by the buffer area. Building information for 2018 was extracted from the 'Addresses and Building Register' maintained by the Dutch land register.

Street connectivity refers to the design of the road network. We included all intersections within the buffers. Road network nodes were mapped from the 2018 TOP10NL topographical dataset. The greater the number of intersections, the better connected (and thus accessible) street segments were considered to be.

2.6. Average snack and soft drink consumption outcome

We included the consumption of three types of products as outcome variables in our analysis, namely daily soft drink consumption, daily small snack consumption, and daily large snack consumption. Soft drinks included all types of fruit juice (fresh or packaged), soft drinks, soda, and lemonade with sugar, except for 'light' variants, which did not contain sugar. 'Small snacks' were exemplified by a few licorice pieces or wine gums, a piece of chocolate, a small biscuit, a handful of crisps or other snacks, or a 'bitterbal' (typical Dutch fried snack). 'Large snacks' were exemplified by a large biscuit, a chocolate bar, a slice of cake, or a bag of crisps. Single servings were defined as 200 mL for soft drinks, one or two pieces or handfuls for small snacks, and one piece for large snacks.

For each dietary outcome, the baseline questionnaire included a question on the frequency and quantity of consumption (e.g., for small snacks: 'How many days a week do you usually eat small snacks?'). Frequency of consumption was measured on a 9-point Likert scale with values ranging from: 0 = '(almost) never', 0.5 = '1–3 days per month', 1 = '1 day a week', 2 = '2 days a week', 3 = '3 days a week', 4 = '4 days a week', 5 = '5 days a week', 6 = '6 days a week', and 7 = 'everyday'. Response options for the quantity of consumption items were 0.5 = 'less than 1 serving', 1 = '1 serving', 2 = '2 servings', 3 = '3 servings', 4 = '4 servings', 5 = '5 servings', and 6 = 'more than 5 servings'. We multiplied the response values for both questions and divided them by 7 to estimate the respondent's daily consumption of soft drinks, small snacks, and large snacks (Mujcic and Oswald, 2016). The outcomes were self-reported prior to the GPS data collection and they represented participants' typical daily consumption of snacks and soft drinks.

2.7. Statistical analyses

The analytical sample consisted of 67 participants with 488 commuting trips. Descriptive statistics, including the median and the first (Q1) and third (Q3) quartiles, were used to summarize the trip characteristics, environmental exposures, and food outlet exposures along the GPS-tracked and shortest-path routes. Paired Wilcoxon signed-rank tests examined food outlet exposures and environmental exposures along the two routes. Wilcoxon rank sum tests were used to test the statistical differences in dietary intakes between the whole and retained sample and trip characteristics between active travel trips (i.e., walking and cycling), car trips, and public transport trips (i.e., train/bus/tram).

Regression analyses were performed at the individual level as the daily dietary intake variables were person-based. Since these outcome variables were interval censored (i.e., the response had to be between 0 and 6), we employed covariate-adjusted Tobit regression models to assess the associations between each daily dietary intake outcome and food outlet exposures along observed and modelled routes. Based on the baseline survey, models adjusted for age (in years), sex (male, female), education level (low [up to lower secondary education], medium [up to upper secondary education], high [university education and above]), marital status (married, never been married, unmarried), monthly household income (low [<€2000], medium [€2000 - €4000], high [>€4000]), and household type ((un)married cohabitation without child (ren), (un)married cohabitation with child (ren), single without child (ren), single with child (ren), others). We did not include ethnic origin because 97% of our participants were Dutch. There were no missing values in these demographic variables. The analyses were conducted using the R software, version 4.1.2 (R Core Team. R, 2021).

3. Results

3.1. Sample characteristics

Participants, on average, had 7.3 (standard deviation (SD) ± 3.4) commuting trips per week and spent 10 h (SD ± 6.0) at home and 6.2 h (SD ± 4.5) at work locations. Table 1 provides descriptive statistics of the participants. Respondents were predominantly females (85.1%). Their mean age was 32.8 ± 6.2 years, 79.1% had never been married, and 76.1% were highly educated. Most participants consumed slightly more servings of small snacks than soft drinks and large snacks, with small snacks intake exhibiting a greater variation among participants than other products. Wilcoxon tests showed no statistically significant differences in daily intakes ($p = 0.64$ for sugary drinks, $p = 0.59$ for small snacks, and $p = 0.87$ for large snacks) between the entire ($N = 143$) and the retained sample ($N = 67$).

Fig. 2 compares food outlet exposures along GPS-tracked and shortest path routes. Median absolute food outlet exposures were higher for 250 m buffers than for 100 m buffers. Compared to the shortest path route, median absolute food outlet exposures along the GPS-tracked route were significantly lower ($p < 0.01$ for 100 m buffers; $p < 0.05$ for 250 m buffers). Regardless of the buffer sizes, relative food outlet exposures along the two routes showed no statistically significant differences.

Table 1
Characteristics of the FoodTrack study participants included in selective daily mobility bias analyses ($N = 67$).

Category	n (%)/mean (SD)
Number of trips	7.3 (3.4)
Age (years)	32.8 (6.2)
Sex:	
Male	10 (14.9%)
Female	57 (85.1%)
Education level:	
Low	2 (3.0%)
Medium	14 (20.9%)
High	51 (76.1%)
Marital status:	
Married	11 (16.4%)
Never been married	53 (79.1%)
Unmarried	3 (4.5%)
Household income:	
Low (<€2000)	14 (20.9%)
Medium (€2000-€4000)	31 (46.3%)
High (>€4000)	22 (32.8%)
Household type:	
(Un)married cohabitation, without child (ren)	22 (32.8%)
(Un)married cohabitation, with child (ren)	16 (23.9%)
Single, without child (ren)	23 (34.3%)
Single, with child (ren)	2 (3.0%)
Others	4 (6.0%)
Daily dietary habits (glasses/day, servings/day)	
Soft drinks intake (Median (Q1, Q3))	0.1 (0, 0.4)
Small snacks intake (Median (Q1, Q3))	1.7 (0.7, 2.6)
Large snacks intake (Median (Q1, Q3))	0.3 (0.1, 0.4)

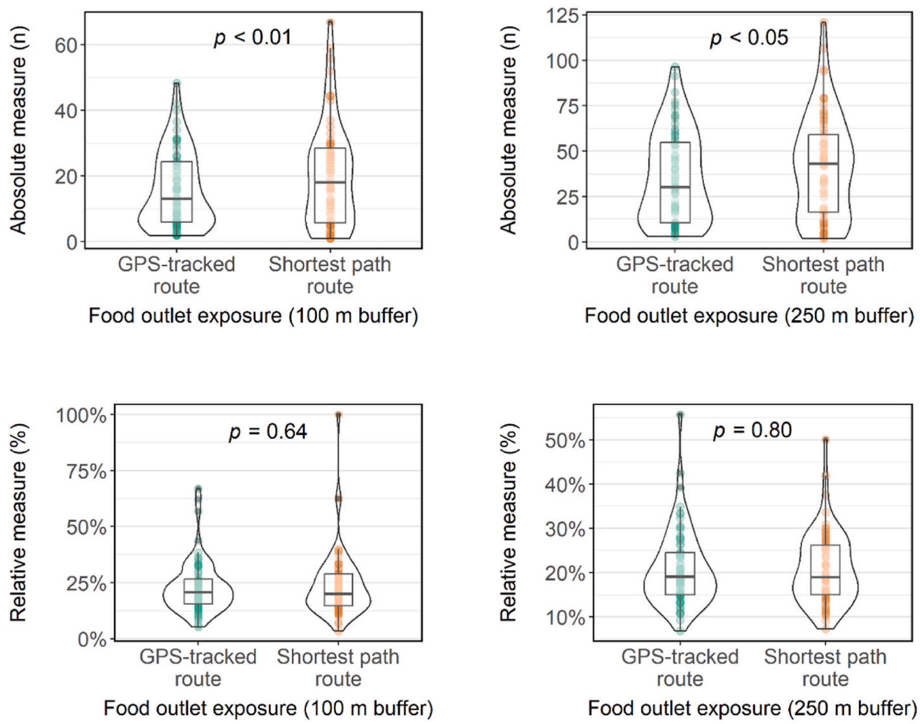

Fig. 2. Differences in individual-level food outlet exposures along GPS-tracked routes and shortest path routes across 100 m and 250 m buffers in the FoodTrack study ($N = 69$). Mean differences were statistically tested by means of paired Wilcoxon signed rank tests.

3.2. Characteristics of the commute trips and food exposures

Table 2 summarizes the descriptive statistics of the commute trips. Median GPS-tracked trip lengths, at 8.3 km, were longer than the median shortest path routes at 6.6 km. The median detour percentage from the shortest path route was 9.1%. Trip characteristics significantly differed between travel modes. Active travel trips were significantly shorter than other trips, while public transport trips had the longest length but with the least detour percentage.

All GPS-tracked commute trips had environmental exposures that differed significantly from those on the shortest path routes (see Supplementary Tables S1 and S2). GPS-tracked routes of all travel had more green space and lower exposure to building density than the shortest path route. Moreover, less connectivity (i.e., fewer intersections) was observed for active travels on the GPS-tracked route compared to the shortest path.

Table 2
Descriptive statistics of trip characteristics for active travel trips ($N = 242$), car trips ($N = 196$), public transport trips ($N = 50$), and pooled ($N = 488$) in the FoodTrack study. Mean differences between active travel trips, car trips, and public transport trips were statistically tested by means of Wilcoxon rank sum tests and were all significant ($p < 0.01$).

Characteristics	GPS-tracked route	Shortest path route
Length (km)		
Active travel trips (Median (Q1, Q3))	5.6 (2.9, 7.9)	5.1 (2.5, 6.4)
Car trips (Median (Q1, Q3))	15.0 (7.5, 33.8)	9.3 (6.5, 31.6)
Public transport trips (Median (Q1, Q3))	39.3 (18.2, 43.1)	39.0 (18.3, 41.1)
All trips (Median (Q1, Q3))	8.3 (5.3, 19.7)	6.6 (4.5, 17.7)
Detour (%)		
Active travel trips (Median (Q1, Q3))	6.9 (2.2, 15.5)	
Car trips (Median (Q1, Q3))	15.6 (7.8, 31.6)	
Public transport trips (Median (Q1, Q3))	1.1 (0.3, 3.6)	
All trips (Median (Q1, Q3))	9.1 (2.5, 22.5)	

The absolute and relative measures of food outlet exposure along the GPS-tracked versus shortest-path routes were compared for active travels, car trips and public transport trips (Fig. 3). For car trips, median absolute food outlet exposures on the shortest-path routes were always significantly higher than on the GPS-tracked routes. There were small but significant differences in median absolute food outlet exposures for active travel. Unlike in the case of active travel, the relative food outlet exposures on the GPS-tracked versus shortest path routes were not statistically different for car trips within the 100 m and 250 m buffers. Results for public transport trips were mixed.

3.3. Associations between food exposure and average consumption of snacks and soft drinks

Fig. 4 summarizes the associations between the absolute and relative food outlet exposure along the GPS-tracked routes and shortest path routes across buffer sizes and average consumption of soft drinks, small snacks, and large snacks. Full numeric results are provided in Supplementary Tables S3–S5. All food outlet exposures based on the shortest path route were insignificantly associated with any daily dietary intakes and so do the absolute measure of food outlet exposure along all routes. However, the relative measure of food outlet exposure along the GPS-tracked routes within the 100 m and 250 m buffers was significantly associated with soft drink intake. In other words, participants with higher food outlet exposures consumed fewer soft drinks.

4. Discussion

4.1. Main findings

We investigated whether SDMB may affect the associations between food outlet exposure and average daily small snack intake, large snack intake, and soft drink intake among Dutch adults. Our findings did not provide evidence of SDMB in the food environment-food intake relationship along commuting routes in the Netherlands. Although people commonly deviated from the shortest commuting route, purchasing

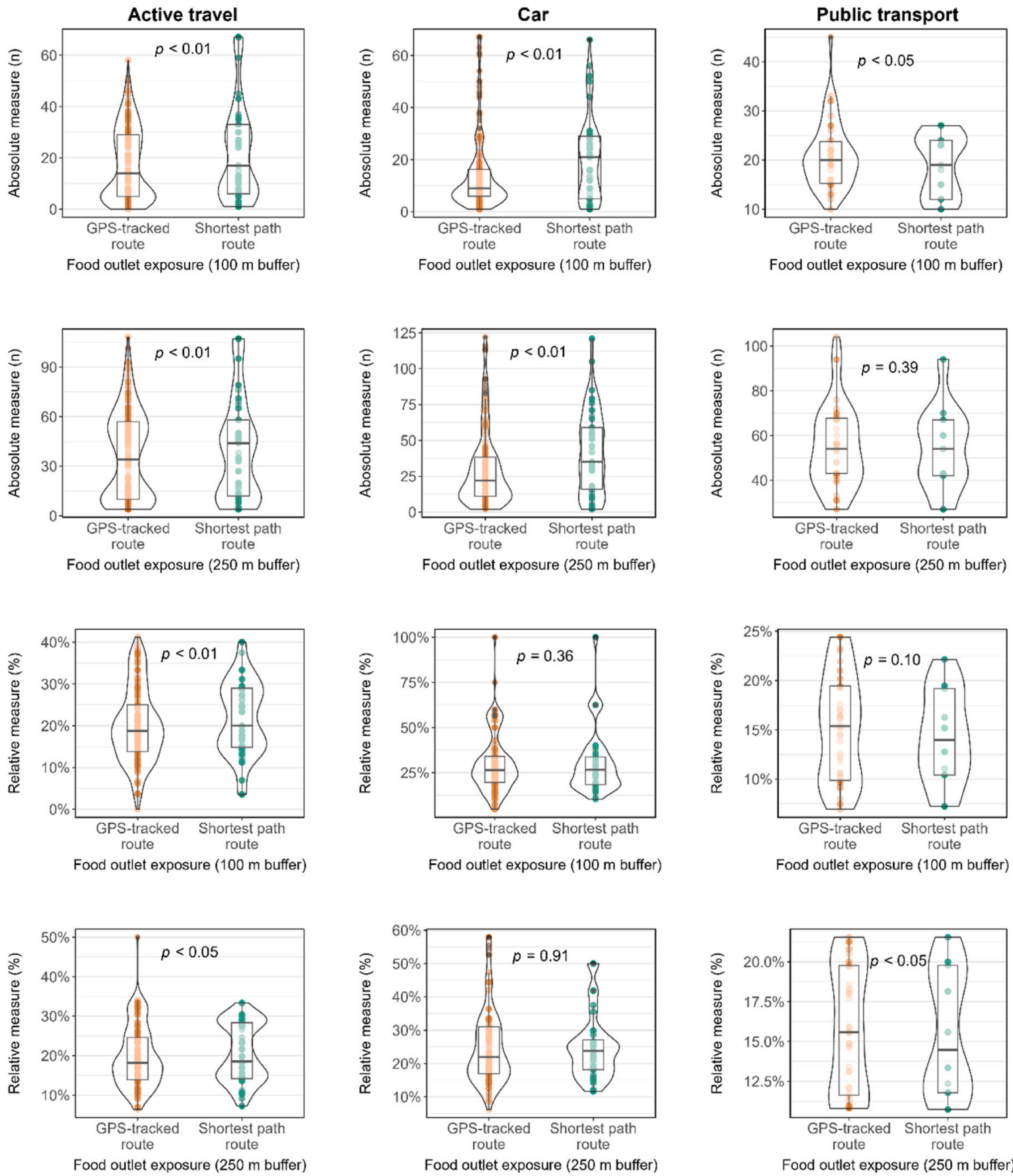

Fig. 3. Differences in trip-level food outlet exposures along GPS-tracked and shortest path routes for active travel trips ($N = 242$), car trips ($N = 196$) and public transport trips ($N = 50$) in the FoodTrack study. Mean differences were statistically tested by paired Wilcoxon signed-rank tests.

snacks and soft drinks appeared not to be the cause.

We found that trip characteristics and environmental exposures differed between traveling actively, by car and by public transport. People making car trips typically travelled along routes with lower building density, while active travellers tended to choose routes with less street connectivity. In contrast to our first hypothesis, the absolute food outlet exposures based on the GPS-tracked routes were significantly lower than those along the shortest paths. No statistical differences were observed regarding relative food outlet exposures between the two routes. Therefore, our results tentatively suggest that the shortest path between activity locations may accurately approximates people's exposure on their actual routes when using the relative measure of exposure to food outlets. However, these findings varied across travel modes. The differences in absolute food outlet exposures between the GPS-tracked and the shortest path routes were higher for car trips than active travel. We found null associations between all dietary outcomes and all measures of food outlet exposures along the shortest path route. Only soft drink intake was observed to be significantly associated with relative food outlet exposures on the GPS-tracked routes. These negative associations were unexpected and ran counter to our second hypothesis.

4.2. Different aspects of the food environment along commuting routes

Our findings showed that, on average, GPS-tracked routes were 30% longer (median = 9.1%) than the shortest paths in terms of all travel, which replicated earlier findings from Luxembourg (21%) (Klein et al.,

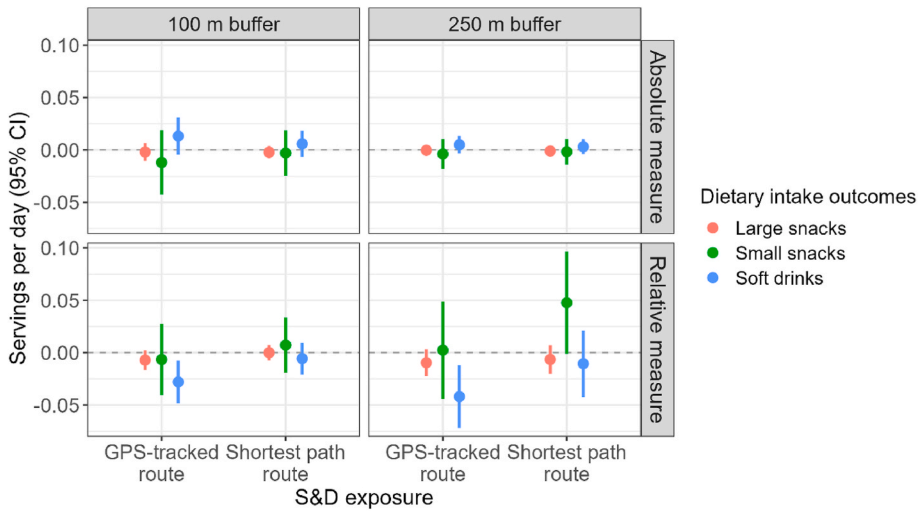

Fig. 4. Regression coefficients (i.e., servings per day) and 95% confidence intervals (CIs) for the absolute and relative food outlet exposures along the GPS-tracked route and shortest path routes associated with daily average soft drinks, small snacks, and large snacks intakes across 100 m and 250 m buffers in the FoodTrack study ($N = 67$). Model was adjusted for age, sex, education level, marital status, monthly household income, and household type.

2021) and Cambridge (UK; 27%) (Dalton et al., 2015). Commuters chose routes with more green space and greater street connectivity over all travel modes. Our results on trip characteristics and environmental exposure along travelled routes corroborated evidence from previous studies (Klein et al., 2021; Krenn et al., 2014).

We found that the absolute food outlet exposure on GPS-tracked routes was significantly lower than that of shortest path routes for active travel and car trips, as reported in earlier studies (Burgoine et al., 2015; Dalton et al., 2015). The active travel routes had higher building density, featuring more food outlets. Although people could make detours, absolute food outlet exposures were similar at the trip level. However, GPS-tracked routes of car trips might bypass highly urbanized inner-cities compared to the shortest path routes, due to the preference for more travel-friendly (e.g., faster and less congested) environments (Klein et al., 2021). Consequently, the absolute numbers of food outlets on GPS-tracked routes were lower than along the shortest paths. Considering people drive longer distances than actively travel, the difference in the absolute food outlet exposure between different routes for car trips can be larger than active travel trips. Besides, the mixed results for public transport trips could be attributed to the fact that people have less freedom to choose routes, thus, the results only reflected the foodscape along certain public transit routes.

No significant differences were observed regarding relative food outlet exposures at the individual level. Relative food outlet exposures reflected the availability of competing food outlets within the buffer. These co-located food outlets could be attributed to the small size of Dutch cities and the consequent high density of food outlets within the urban areas. Another factor is that food outlets often congregate at locations with the greatest potential client density. However, it should be noted that shorter trips within Dutch cities engender significant differences in the relative food environment compared to longer trips or trips including detours through urban areas.

4.3. *Selective daily mobility bias in the food environment*

Corresponding to previous studies (Roy et al., 2019; Shareck et al., 2018), we found null associations between small and large snack intake and all food outlet exposures on two routes. However, we unexpectedly observed negative associations between relative food outlet exposure along 100 m and 250 m buffered GPS-tracked routes and average daily soft drink intake. Possible reasons for this finding could be three-fold. First, the food outlet exposure might not include some potential locations where people could obtain soft drinks. Although we included the most important locations for purchasing snacks, we could not exclude the possibility that other avenues for obtaining snacks, such as vending machines, online purchases, or snacks or drinks received from family/friends, could have been impossible to acquire or unsuccessfully geocoded (Mackenbach et al., 2022). Nevertheless, the geocoded food outlets we used in this study were field confirmed to be accurate and reliable for food studies. Second, participants might have responded differently to the survey questions due to different levels of knowledge of soft drinks (Rampersaud et al., 2014). For example, the perception of whether diet soft drinks (e.g., Diet Coke and Diet Pepsi) are sugary is mixed (Rampersaud et al., 2014). Consequently, the reported consumption of soft drinks could differ between participants. Third, this population group could be less interested in consuming soft drinks, which was reflected by the low level of soft drink intake. Therefore, our observed counterintuitive association may be accidental.

Consistent with Burgoine et al. (2015), we found no evidence of a SDMB in the food environment regarding snacks and soft drinks along commuting routes in this sample. People tended not to make detours for the purpose of obtaining snacks or soft drinks. As a result, it is unlikely that utilizing GPS-tracked commuting routes in snacks and soft drinks related food studies will result in SDMB. We note, however, that collecting GPS data for large populations is typically less practicable for many reasons, including high cost and many participants' reluctance to be tracked. Therefore, surveys recording people's activity locations remain popular as alternative data sources (Burgoine and Monsivais, 2013; Burgoine et al., 2014; Mackenbach et al., 2023). When using survey data, the travel routes between activity locations can only be simulated using the shortest path routes (Burgoine et al., 2014). Although our study showed that compared to the GPS-tracked route, the absolute food outlet exposure along the shortest path routes was significantly higher, the relative exposure was similar on both routes. Thus, measurement of the relative exposure to food outlets on shortest path routes might provide adequately accurate estimates of the relative exposure participants would experience on potential actual GPS-tracked routes. Despite ongoing debates on the effectiveness of such relative measures (Shareck et al., 2018; Burgoine et al., 2018; Thornton et al., 2020), applying a relative measure of food outlet exposure could provide a new lens for understanding the food environment. It is worth noting that the relative measure should also be tested in other environmental settings (i.e., other countries or target food outlets). Different foodscapes or food outlet distributions could potentially significantly influence the usage of relative measures.

Our finding that a SDMB might not exist only applies to studies on the food environment of snacks and soft drinks during commuting. Previous studies have confirmed SDMB for other exposure-outcome relationships (e.g., sports practices and accessibility to sports facilities) when people actively visit locations (Perchoux et al., 2016; Shrestha et al., 2019). However, the food environment appears not to encourage people to make snack-related detours, whereas environmental exposures do induce detour-making behavior (Klein et al., 2021; Dalton et al., 2015; Krenn et al., 2014). Since these two environments are intertwined, disentangling their interaction is the key to a better future understanding of SDMB-related effects. First, though many transport studies have revealed individuals' preference for route choices (Noland and Thomas, 2007; Kestens et al., 2018; Verhoeven et al., 2018), how people weigh route characteristics (e.g., safety, less congestion) and the motivation to purchase food remains unknown. In our sample, participants' preference for commuting routes' environmental characteristics might outweigh the motivation to purchase snacks or soft drinks, and thus our results didn't provide evidence of a SDMB. However, other types of food outlets may have a stronger attraction to people over the route characteristics and may lead them to detour. A possible way to unravel such an attraction could be done by comparing the route when people actually purchase food and the most frequently used commuting route. A commuting route a person used most frequently could be a reflection of people's trade-offs between route environmental characteristics and available food outlets along the route. Those trips deviating from the most frequent commuting route could explain why people detour. However, it should be noted that such analysis requires a more nuanced study design (e.g., using measures of food consumption or purchases at the trip level), additional information on individuals' motivation of route choices, a larger sample size, and longer tracking duration. Second, our study was only limited to commuting and excluded other trip purposes (e.g., shopping, leisure). People may have more freedom and willingness to detour for purposes in such a non-commuting travel environment than the highly repetitive and routinely commuting trips.

4.4. Strengths and limitations

This study was among the first to examine the influence of SDMB in the food environment using new free-living mobility data by focusing specifically on the consumption of snacks and beverages. We broke new ground by depicting the food environment along commuting routes from the food environment's absolute and relative perspectives, which provided a more comprehensive understanding of how SDMB might influence food exposure. Moreover, this study linked exposure to food outlets to people's average daily food consumption, which might provide a closer causal relationship between exposure and food consumption versus the exposure-body mass index relationship (Burgoine et al., 2015).

This study also had some limitations. First, as already criticized by a review (Cetateanu and Jones, 2016), we used a relatively small sample with primarily female participants. Consequently, our results may likely not apply to other population groups, and replications in larger or more representative population groups are needed. Second, since our respondents primarily resided in urban areas, signal reception might have affected the GPS data quality (e.g., dense tree canopy and tall buildings). Some commuting trips could be missed, potentially impacting exposure assessments. However, this impact was likely negligible due to the Netherlands' paucity of high-rise urban canyons. Third, home and work locations were estimated from the GPS data, which may face some displacement errors. However, given the smartphone's GPS accuracy (Merry and Bettinger, 2019), the influence of such displacement is supposed to be minor. Fourth, the baseline questionnaire on respondents' dietary intakes was a crude measure collected prior to the GPS tracking. Such a temporal mismatch between exposure and outcome could potentially affect the associations between daily intake of soft drinks and food outlet exposure. However, the food frequency questionnaire has been shown to be a valid tool to estimate the frequency of or portion size of dietary intake over a period of time (Willett, 2012; Kim and Holowaty, 2003). Besides, given the fact that commuting is a habitual and repetitive behavior in people's daily life (Deng et al., 2023), GPS-tracked commuting routes could be representative and less subject to change compared to other daily trips to some extent. Therefore, the influence of the temporal mismatch could be limited. Finally, participants in our study were not recruited via random sampling but via online and offline platforms. Although recruitment through these platforms has shown good performance in sample representativeness and effectiveness in sample size (Blom et al., 2017; Loxton et al., 2015), certain groups of people were likely excluded.

5. Conclusions

Our study showed no evidence of a SDMB in the relationship between exposure to food retailers regarding snack and soft drinks along commuting routes and snacks and beverage consumption in this sample. The relative exposure to food outlets on the shortest path routes was sufficiently similar to that on GPS-tracked routes to allow for shortest path route data to act as a potentially surrogate for GPS-tracked route data. It should be noted that our findings might be limitedly generalizable to other food environment and were based on a small but nuanced dataset.

CRediT authorship contribution statement

LW: conceptualization, methodology, formal analysis, visualization, writing—original manuscript. JDM: conceptualization, methodology, data curation, writing—review and editing. MPP: data curation, writing—review and editing, funding acquisition. RV: funding acquisition, project administration. MH: conceptualization, methodology, writing—review and editing, supervision.

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Conflicts of interest

The authors declare that they have no competing interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2023.103088.

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